Hydrous Area Segmentation in Radar Imagery by Level Set-based Snakes

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Abstract

Les travaux présentés concernent la segmentation de zones hydriques par la méthode géométrique des contours actifs. Nous appliquons cette technique à des images radar et établissons un ensemble optimal de paramètres d'opération. Nos résultats montrent une délinéation précise des contours d'une zone hydrique à partir d'un simple pixel d'amorce. Nous montrons que la méthode est très stable par rapport au choix des paramètres ce qui en fait un bon candidat pour une implémentation automatique.

In this work, we present segmentation of flooded area detection in spaceborne SAR images. We show that the geometric snakes method is robust to achieve the segmentation when applied to that kind of images. Our results show an exact segmentation of hydrous area edges from a single pixel seed. We show that the method is robust with respect to parameter values making it a good candidate for an automatic approach implementation.

1 Introduction

An essential hability of any automatic terrestrial interpreter consist in the segmentation of flooded area. The main difficulties with segmentation are often related to the presence of noise in the image or to low contrast edges. Particularly, in radar imagery, most segmentation approaches are sensible to speckle noise. This limitation can be overheaded using filters but with loss on edge precision. An efficient method to recover edges in an image with such characteristics is based on active contour snakes.

Historically, the active contour method was developed by assuming that the contour corresponds to locations of significant intensity change [1] and by adding smoothness constraint in attempt to regularize the problem [2]. So, one starts with an initial contour and then looks for admissible deformations which let it evolve towards the desired contour [3]. As pointed by Caselles et al. [4], the parametrization of the curves in the classical approach do not allow to get the geometrical regularity of the contours. To solve this problem, they proposed a new approach based on level set. Their work is based upon the algorithm developed by Osher and Sethian to track the motion of fronts propagating with curvature-dependent speed [5]. Furthermore, the level set-based approach presents the advantages that the initial snakes can be far to the final state and that it can have a different topology.

In the present work, we present segmentation by level set-based snakes. We use the general model proposed by Yezzi et al. [6]. This approach is applied to the segmentation of flooded area in spaceborne SAR images. We show that the method is robust with respect to parameter values and gives an exact segmentation of hydrous area edges.

In the next section, we describe the formalism of the level set-based snakes. Beginning with a brief description of the classical snakes approach, we describe the extension made by Osher and Sethian [5] and by Caselles et al. [4] when they introduced the level set version. Then, in the third section we describe the application of the level set-based snake method to radar images. We focus on hydrous area segmentation. From our results, one can consider this method as a good candidate for an automatic approach implementation.

2 Active Contours

2.1 Classical Snakes

The classical formulation of snakes involves a simple paradigm based on the minimization of an energy function. Generally speaking, the method consists in associating to a parametric curve $C(\gamma)$ in a two-dimensional-image (represented by the pixel coordinates, $(x,y) \rightarrow \gamma \in [0,1]$) an energy $E(C)$ that is assumed to take the form

$$E(C) = E_{\text{int}}(C) + V(C) \tag{1}$$

The term $E_{\text{int}}(C)$ is the internal energy of the curve and is independent of the underlying image. Essentially, it weights the rigidity and tension of the curve and controls in some sense the inherent smoothness of the curve. One can descibe it as a regularization term. The potential $V(C)$ depends on the image (i.e. the pixel intensity $I(x,y)$).

Finding the optimal contour is typically done by adding dynamics to the snake. If we allow the curve to have local deformations, then using the Lagrangian formulation for $E(C)$, we can minimize the action and find a corresponding dynamical equation of motion. One then starts with an initial snake and lets it evolve until some suitable conditions are satisfied, i.e. until a local minimum of the potential is reached.

The main problem is that there can be (and there usually is) more than one minimum for $V(C)$. Typically, there are local minima associated with noisy points, which are punctual in the image (having a small area). The advantage of snake formulation is that since the dynamics is controlled by the image, but also by a snake tension, we can adjust the different energies associated with a configuration such that the local minimum will be avoided and the snake will asymptotically flow towards the global minimum. In some sense, we can think of a snake as an elastic band; when a local tension builds up caused by a local impurity, then it eventually steps over the impurity. If, on the other hand, the obstruction is more macroscopic, then it stops there.

This classical approach has been supplanted by geometric snakes for many reasons, one of them is that the solution is not very stable and the initial snake needs to be close to the contour to detect [4]. Moreover, it does not allow for splitting or merging of snakes which makes the approach inefficient when there are topologically non-trivial contours in an image. The idea proposed by Caselles et al. [4] to bypass this difficulty consists in geometrically embedding the formulation of the two-dimensional curve in three dimensions, i.e. by considering the two-dimensional curve as a slice of a surface in a three-dimensional space. The advantage is that topologically the surface remains connected when the two-dimensional curve gets disconnected.

2.2 Level Set-based Snakes

Geometric snakes, to be used here, are based on a level set representation of a curve and can be seen as curvature dependent propagating fronts under the influence of a scalar potential.

The basic idea is to consider active contours as a given level of a dynamic surface.

$$\vec{C}(\gamma,t) = \{(x,y)|\psi(x,y,t) = 0\} \tag{2}$$

So one have to build a differential equation to describe the evolution of the continuous surface given by ψ. We want it to be such that the zero level is attracted by the edge in the image. So, the surface value have to cross the zero level when the surface crosses the edge of a given object in the image. The geometric formulation of snakes is based on Euclidean curve shrinking equation. Essentially, this equation governs the dynamics of a curve through

$$\frac{d\vec{C}}{dt} = \kappa\hat{N} \tag{3}$$

where κ is the scalar curvature and $\hat{N}$, the inward unit normal to the curve. This equation is such that the flow of the Euclidean curves maximize the shrinking as time goes on. Another useful property is that the evolution is such that the curve converges to round points without developing singularities as it flows. Physically, we can think of this equation as reducing the protuberances of the curve faster than it does for the uniform parts while shrinking the perimeter. As in the classical approach, the evolution equation can be obtained by an energy optimization: simply by associating the internal energy to the length functional of the parametrized curve:

$$L = \int_0^1 \left|\frac{d\vec{C}}{d\gamma}\right| d\gamma \tag{4}$$

There is not a unique way to extrapolate eq. (3) on the surface outside the zero level. Following Osher and

Sethian [5], we introduce the inverse mapping function, $f(x,y)$, defined by

$$\kappa^2 \left|\nabla f(x,y)\right|^2 = 1 \tag{5}$$

Then we choose the evolution of the surface to be given by $\psi(x,y,t) = c$, where $t = f(x,y)$ for any fixed constant c. As a result, one gets from eq. (3)

$$\frac{d\psi}{dt} = -\frac{d\vec{C}}{dt} \cdot \nabla\psi \tag{6}$$

$$= \left|\nabla\psi\right| \nabla \cdot \left(\frac{\nabla\psi}{\left|\nabla\psi\right|}\right) \tag{7}$$

2.3 Image Information Representation

The eq. (7) do not take into account the information present in the image. To add this information, one has to introduce an image dependant metric, ϕ, in the length functional.

$$L_\phi(\vec{C}) \equiv \int_0^1 \phi \left|\frac{d\vec{C}}{d\gamma}\right| d\gamma \tag{8}$$

$$= \int_0^1 \left|\frac{d\vec{C}}{d\gamma}\right| d\gamma - \int_0^1 \frac{\alpha \left|\nabla(G*I)\right|^n}{1+\beta\left|\nabla(G*I)\right|^n} \left|\frac{d\vec{C}}{d\gamma}\right| d\gamma \tag{9}$$

On the second line, one can recognize the Euclidean length previously introduced, eq. (4). The second term is the potential as introduced by Kass et al. in the classical approach [3] but with an exponent n and with a denominator to cut the effect of large gradient. The function G appearing in the last integral denotes the presence of a filter applied on the image. Typically, one chooses the constants $\alpha = \beta = 1$ and then is left with the following metric:

$$\phi(x,y) = \frac{1}{1+\left|\nabla(G*I)\right|^n} \tag{10}$$

In that form, $\phi \approx 0$ on an edge and $\phi \approx 1$ over a perfect uniform region. Minimizing the metric dependent length, eq. (9), and substituting variables, we get

$$\frac{d\psi}{dt} = \phi\left(\nabla \cdot \frac{\nabla\psi}{\left|\nabla\psi\right|} + \nu\right)\left|\nabla\psi\right| + \nabla\psi\cdot\nabla\phi \tag{11}$$

where we have added a constant advection term, given by ν, which causes a constant contraction/inflation of the front for positive/negative values respectively. The effect of the last term is to attract the evolving contour as it approaches an edge and to push the contour back out if it passes the edge.

Using the formulation above, one of the main advantage of this method is that it allows the numerical implementation over a discrete grid in the (x,y) plane, which is not the case in the standard formulation. However, still some problems remain it we try to discretise the set of equations naively by using a central difference scheme. As discussed by Osher and Sethian [5], one needs to respect an entropy criterion in order to ensure the continuity of the evolution. The solution to that problem has been discussed extensively in [5] and it requires to separate the level set equation above in two parts:

$$\frac{d\psi}{dt} = F_0 + F(\kappa) \tag{12}$$

where F_0 is the part not depending on the curvature and $F(\kappa)$ the part depending on it (these terms can be viewed as forces). Then the entropy criterion is satisfied if one approximates the constant advection term ν by using upwind scheme and the rest using standard central scheme (this is described in details in [7]). The latter scheme is a generalization of Godunov's method [5] and has been builded such that the fronts propagate minimizing shocks.

In addition, let us mention briefly that an apparent drawback of the formulation is that the numerical calculation of the front evolution requires updating $O(N^2)$ points for an $N \times N$ image. This can be substantially reduced by updating only points close to the zero level set [7], which we have done in our implementation.

As initial conditions for the level set evolution, we use a cone centered on a point (x_0, y_0) of the form:

$$\psi(x,y) = \sqrt{(x-x_0)^2 + (y-y_0)^2} - d \tag{13}$$

where the zero level set is situated at distance d from the center. So, the level set is chosen to be negative inside the snake and positive outside it.

The total number of parameters necessary for a given segmentation is three (without counting parameters associate with filters and with the initial condition). Let us briefly describe these parameters:

- ν: this is the parameter appearing directly in the level set evolution equation. This is the advection term, when it is negative the snake will expand whereas when it is positive, it will shrink. The first case is useful when we want to segment contours from the interior of a pattern.

- Δt: when the evolution equation is discretized in time, we need to set a scale of evolution. The value of this scale comes from experience (hidden here is the fact that we use unit spatial steps, $\Delta x = \Delta y = 1$). If we allow it to be too big, then the snake will evolve in steps too large to be under control in the image and typically it will step over edges. When it is too small, the snake will take too many iterations to move significantly in the image.

- n this parameter controls the metric ϕ described above. Typically it affects the dependance of the metric on the contrast in the image. The typical value is $n = 2$ but, as we will describe below, for certain very low contrast cases, $n = 4$ is also useful.

Although this seems to be a lot of adjustable parameters, their values remain very stable for identical types of images: the snakes developed here are very stable and we believe they could form a good base for automatic segmentation.

3 Application to radar images

The first application (figure 3) is an Airborne SAR image of the Antigonish region between eastern part of Nova-Scotia (Canada) and Cape-Breton Island [8]. The image has been acquired in C-band using a HH polarization with a resolution of 15.6 m/pix. The image size is 1122×434 pixels. The goal is to extract the coastline.

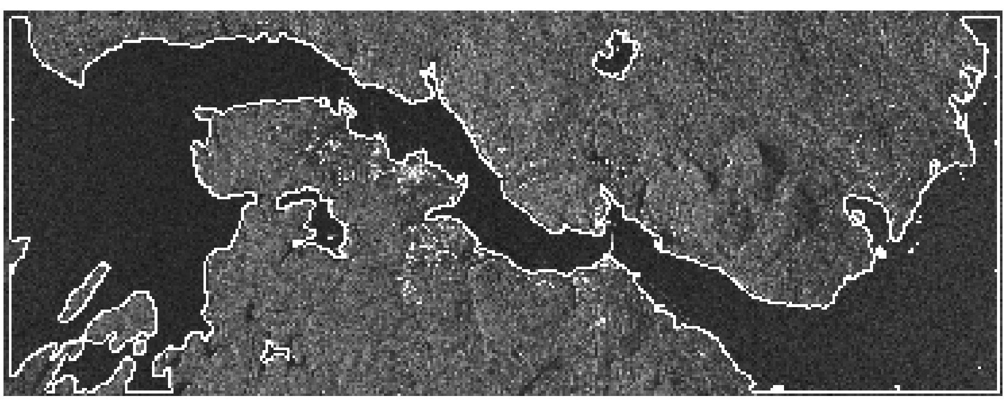

Figure 1: *Snake evolution after 1250 iterations for an experiment of coastline detection*

We have to deal with a pattern (hydrous area) that is very dark and uniform with coastlines being sharp at some places, noticeably in the center of the image, but being very blurry on the right hand side. So, in constructing the metric we have to choose a high exponent (see eq. 10). We chose $n = 10$, with a standard deviation of $\sigma = 3.0$ for the gaussian filter. The parameters directly associated with the snake evolution are the time discretization, $\Delta t = 0.1$, and the advection term. The hydric area being more uniform than the terrestrial area, we put the initial snakes in the hydric area and choose the advection term such that the snakes inflate as time goes on, $\nu = -2$. We choose a small value for this advection term such that the snakes does not evolve throught the blurry coastlines on the right side.

The results presented in figure 3 has been obtained on a 300 MHz Pentium and has necessitate 1250 iterations, 150 seconds of CPU time. We used 15 initial snakes with a radius of 2 pixels distributed uniformly in the hydric area. We observe that the coastline has been properly segmented by the snakes. One can observe the precise segmentation of the small islands in the down left part.

Figure 3 (a) shows a Radarsat-I image of a portion of the Winnipeg area during the Red River flood in 1997 [9]. The image shows water (black areas) over fields. The image has been acquired in standard mode at a resolution of 12.5 m/pix. The image size is 900×701 pixels. The goal here is to find the limits of the flooded areas, which in this image are the black areas. In addition to speckle noise, there is a lot of interference objects (in particular roads) for contour extraction of flooded areas in the image. We start the process using 23 initial circular snakes as shown in figure 3 (a). As previously, the initial snakes has been placed in the hydrous area which is more uniform. As one can see, the region limits are highly non-trivial and our starting snakes are far from the segmented image.

As previously, we have chose $\Delta t = 0.1$ as time discretisation. The standard deviation is $\sigma = 0.5$. For the other parameters, we have made many experiments to show the stability of the method, see figures 3 (b)-(f). Every experiment has been done with inflationary snakes, but with an advection term going from $\nu = -4$ to $\nu = -10$. As one could see, the last value is too high and the snakes don't stop at the edges of the flooded area but go through the terrestrial areas. We have also experimented the effect of varying the metric exponent from $n = 2$ to $n = 8$. This last parameter as no important effects on the snake evolution.

The advection term seems to be the most determinant parameter. The results and the number of iterations both depend on it. For values between $\nu = -4$ to $\nu = -8$, the results is quite stable, but for higher values, the snakes fail to stop at the edges. The number of iterations decreases almost linearly with the value of the advection term going from 500 iterations at $\nu = -4$ (80 seconds of CPU time on a 300 MHz Pentium) to 150 iterations at $\nu = -10$ (18 seconds of CPU time on a 300 MHz Pentium).

4 Conclusion

In this paper, we have demonstrated the applicability of level set-based snakes, for contour segmentation in radar images. This approach have important advantages over the standard snakes approach:

- initial snake position can be far from the final state,
- snakes can merge and split,
- various parameters make level set-based snakes more flexible to various image types,
- they are more robust to noise.

Last point is a very important one for coherent imaging like radar. Edge detection is always a difficult problem in SAR images which usually require extensive image pre- and post-processing. Our experiments show that level set-based snakes seem to be a viable alternative to edge detection techniques in SAR images, especially for semi-automatic water-terrain separation. In addition, when implemented correctly, the computational complexity is quite slow as it is proportional to the snake length, not the image size (snake presented above took not more than two minutes of CPU time to calculate on a 300 MHz Pentium).

Our experiments show that level set-based snakes are of enough pratical interest to deserve further work, especially regarding the automatic aspects of the implementation. For instance, a procedure to find initial ”point” snakes (seed points) over a water area in SAR images could be coupled to the current algorithm in order to provide an automatic coastline detection tool. Other extensions to the present work concern the applicability to other image modalities.

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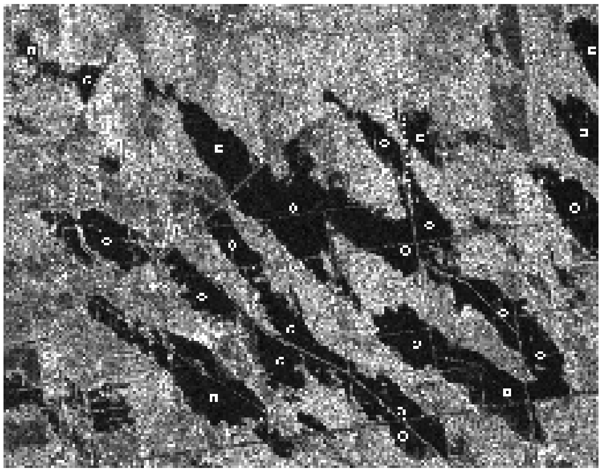
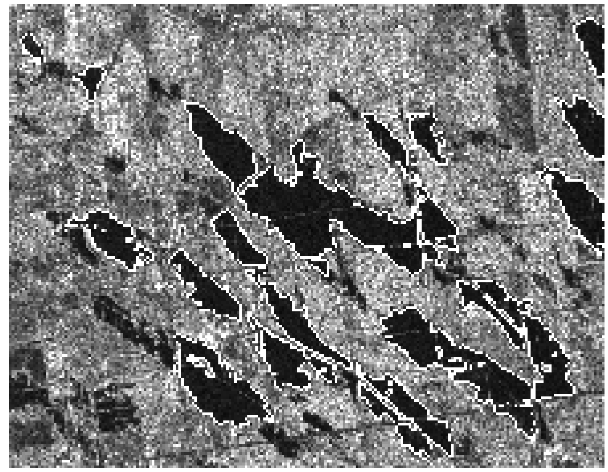
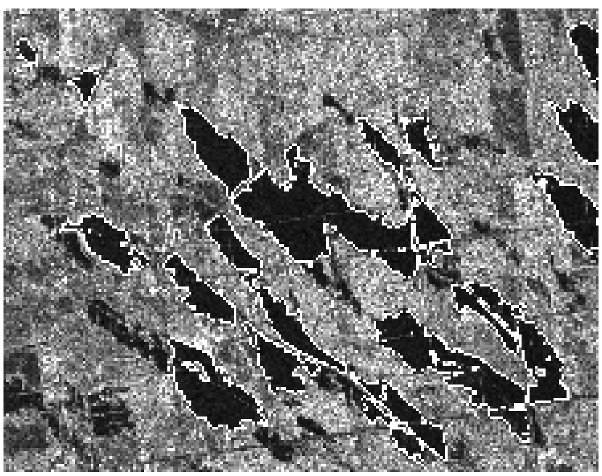


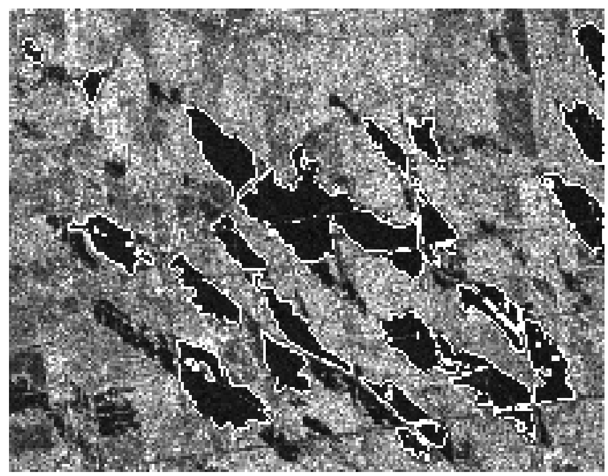
(a) initial state



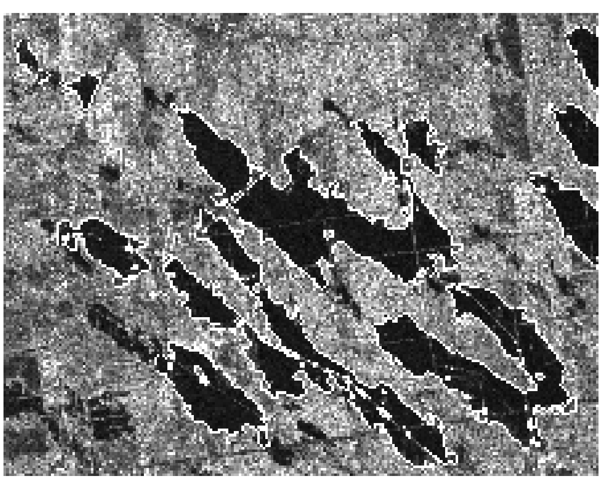
(b) $\nu = -4, n = 4$



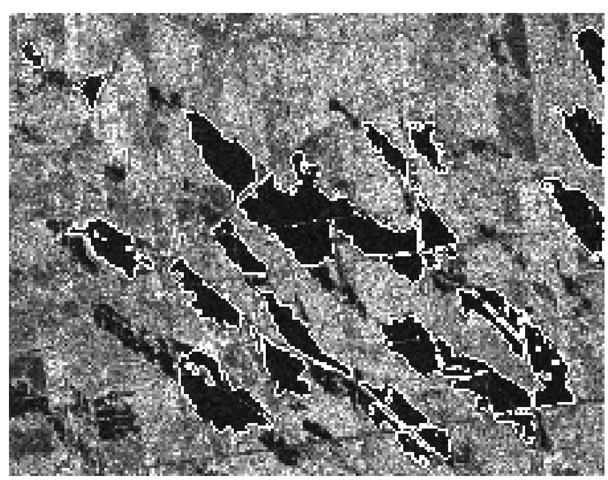
(c) $\nu = -8, n = 4$



(d) $\nu = -8, n = 8$



(e) $\nu = -10, n = 2$



(f) $\nu = -10, n = 8$

Figure 2: *Experiment of flooded areas detection*